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Procedia CIRP 00 (2018) 000–000

www.elsevier.com/locate/procedia

51st CIRP Conference on Manufacturing Systems

A Framework of Integrating Knowledge of Human Factors to Facilitate HMI and Collaboration in Intelligent Manufacturing

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Abstract

Recent developments in the field of intelligent manufacturing have led to increased levels of automation and robotic operators becoming commonplace within manufacturing processes. However, the human component of such systems remains prevalent, resulting in significant disturbance and uncertainty. Consequently, semi-automated processes are difficult to optimise.
This paper studies the relationships between robotic and human operators to develop the understanding of how the human influence affects these production processes, and proposes a framework to integrate and implement knowledge of such factors, with the aim of improving Human-Machine-Interaction, facilitating bi-directional collaboration, and increasing productivity and quality, supported by an example case-study.

Peer-review under responsibility of the scientific committee of the 51st CIRP Conference on Manufacturing Systems.

Keywords: Intelligent Manufacturing; Human-Machine-Interaction; Collaborative Robotics.

1. Introduction

For several decades, the prevalence of automation has increased exponentially, to the extent that autonomous systems are ubiquitous [1], and automation has become an international talking point, that transcends the scientific community. This popularity is the result of multiple factors. Economically, manufacturing accounts for 25% of the German GDP, and represents a considerable portion of the GDP of several other European Countries [2]; the need to retain this industry has led to continued investments in automation to increase productivity and remain competitive. From a social perspective, many of these European Manufacturers are also facing a decreasing workforce due to an ageing population.

Furthermore, the increased capability of automated systems has increased rates of adoption, as the related and dependent fields have grown and enjoyed their own successes and developments. The fields of computer science and AI, Control Systems, Machine Vision, and Robotics, to name a few, have all been subject to intense focus and investment, accelerated in part by the founding of international initiatives, including Industry 4.0 [3]. It is, however, the exponential increase in data generation, collection, and processing [4], which has undoubtedly facilitated this current paradigm shift, and new tools, methodologies and techniques continue to emerge present a number of opportunities to further improve manufacturing processes.

This continued investment in automation has resulted in an interesting period of transition, whereby the presence of automated cells and processes within the manufacturing sector are far from uncommon, but in which the human element of such processes remains dominant. As a consequence, an environment exists, wherein the practices of automation and traditional manufacturing are employed within the same spaces, processes, and products; and human operators frequently collaborate with robotic counterparts within singular product processes. The resultant disparity in capability between robotic operators and their human counterparts is a source of uncertainty and instability, which leads to less than optimal performance. Employing concepts of Intelligent Manufacturing to facilitate these working relationships, can seek to alleviate the effects of this uncertainty, by enabling adaptable behavior, improving Human-Machine-Interaction in such instances.

2. Literature Review

The current volume of literature in this area is extensive, and a large amount of work is being conducted on a global scale, to realize the benefits that the information age has to offer the manufacturing sector. *Intelligent Manufacturing,* as the field has come to be known, is dependent on a multitude of interconnected processes and systems, that exist within a wide range of technical disciplines. However, the unifying factor is the use of data and informatics, to enhance manufacturing processes [5]. The applications are varied, research focuses include: Novel automation control systems, with a focus on, decentralization, virtualization, reconfiguration, and adaptability [6-8]; the development and application of machine learning and artificial intelligences [9]; and virtual and augmented reality systems, which are being used to bridge gaps in geography, knowledge and skill level [10].

Within Intelligent Manufacturing, the utilization of data and computational techniques to facilitate and enhance physical processes has resulted in the development of *Cyber-Physical-Systems(CPS)*; which combine digital processing and planning with physical manipulation. Such systems vary widely in design, but all focus on the utilization of collected data, to generate *knowledge* about the current process and surrounding environment. This knowledge can be used to influence machine behavior. CPS's are typically defined by the degree to which they are able to leverage this knowledge to increase their capability. Simple implementations are able to respond appropriately to disturbances, and advanced systems able to achieve a level of cognitive autonomy capable of advanced planning, adaptation, and self-configuration [11, 12]. Knowledge generation and the use of knowledge to support decision making is typically provided within the CPS architecture, by machine learning elements. [13, 14]. Use of learning enables non-linear relationships to be modelled, and temporal trends uncovered more easily through the use of historical data.

Collaboration presents several problems for conventional computer architectures which traditionally have centralized and hierarchal structures. As the system complexity grows, centralized processing inhibits the adaptability and autonomy of the system [18, 19]. Systems based on the principles of distributed control have been proposed to overcome this, as they enable complex problems such as task planning and optimization, to be divided into several small problems, distributed to a network of multiple *intelligent agents*. These agents require the capability to autonomously handle efficient and effective *real-time communication* and *negotiation* with other agents, which enables alignment of the behaviors of all constituent operators involved in the process to successfully complete the task [15-17].

In such a way, the use of decentralized control facilitates collaborative behavior. It enables individual operators, to dynamically change their behavior autonomously, in response to external changes, in the behaviour of others and the environment [12, 20]. Providing the capacity for intelligent behaviour through agency necessitates the consideration of agent structure and multi-agent control, and how they can best be utilized to facilitate collaboration. To perform collaboratively, agents interact governed by their own individual goals, motivated by their individual beliefs; but also by collective goals; which must be achieved through cooperation with the other agents. [22].

Within a manufacturing system, intelligent agents may be software based, or, a combination of hardware and software forming a logical unit within the system, or *holon*, as defined by [21]. Each agent is autonomous, having its own sensory inputs, objectives, beliefs, knowledge, and skills, and awareness of distinct internal and external environments, which provides embodiment. The internal structure and behaviour of each agent can be expanded through internal intelligent functions, to provide different functionality, with respect to information received from the external environment.

Embodiment refers to each agent being aware of only the information that it receives based on its own interactions, that is, different instances of agents with an identical structure, will act in different and respectively suitable ways based on their individual cumulative experiences [23]. Additionally, the structure of software-based agents closely resembles that of Object-Oriented programming languages, whereby individual agents may be represented by instances of an object, with internal structures and functions to facilitate their behaviour. Concepts of agency in manufacturing are not new, and detailed overview of the structure, capability, and application of Intelligent agents, can be found in [17, 24].

The use of software to provide agency can be extended to provide the capacity for intelligent behaviour. The implementation of such behaviour and attempts to replicate ideas of *cognition* are referred to as *Cognitive Architectures* and provide an implementation for the management of information. Typically, cognitive architectures are structured around a central communication or *cognitive control* unit, which is responsible for managing the internal *thought processes*. This is enhanced by other extensible *modules* to facilitate necessary behaviors; such as Perception, Learning, Decision-Making, and Memory, as evidenced by existing examples: ACT [25], SOAR [26], and particularly, C4, originally developed for use in video games [27]. This modular structure mimics that of the human brain, and facilitates the integration of low-level perceptual and motor control systems (established standards and processes analogous to perception and motor control exist in the fields of data collection, and robotics respectively), with higher-level knowledge extraction and decision-making processes [28].

Extension of collaborative robotics and intelligent control to tasks involving human collaboration is well studied in terms of physical collaborative efforts. Handling tasks are improved through coordination of robotic and human operator motion. This can be used to increase human strength, enabling handling of large and unwieldy components [29], and facilitating safety when sharing a common work area, through advanced collision detection. Methods of *Direct-Teaching* are also common, which combines the flexibility and configurability of humans with the strength, accuracy, and repeatability of their robotic counterparts. Applications enable autonomous replication of advanced manufacturing processes, such as composite layup, oversize component handling, and welding fabrication [30-33].

A much smaller volume of work has been conducted on more passive modes of collaboration, whereby knowledge of others, combined with context, may be used to inform behavior [34, 35]. As mentioned, the prevalence of human operators is a source of disturbance and prevents many of the traditional optimization techniques employed in automation from being effective. No two operators performing the same task will approach a robotic degree of repeatability in their performance. Humans are understood to rely on a finite reserve of cognitive *resources,* which in current models represent non-specific units used to complete cognitive tasks [36]; In addition, a number of factors are understood to affect the mechanisms by which these *resources* are consumed, contributing to changes in performance, notably: Fatigue [37-39]; Skill Level & Experience [40]; Stress Levels & Emotional State [41]; Environmental Conditions [42]; & Satiety [43]; are all found to have varying impact on task performance. Knowledge of these factors can be used to inform decision-making, and dynamically adjust behavior based on current and predicted performance, between multiple operators; and facilitates optimal control of the robotic elements of the system.

3. A Framework for the Integration of Knowledge of Human-Factors

The literature review highlights a number of areas within manufacturing which may present opportunities. Incorporating intelligence into manufacturing control systems can facilitate adaptable behavior in a complex and dynamic environment. Decentralizing manufacturing control systems, and providing individual robotic operators with their own agency and intelligence, can improve collaborative behavior; through appropriate response in action to observed variation and disturbance.

One of the main gaps in the application of this to Human-Machine Interaction is the consideration of human factors with respect to their influence on performance. This has been a focus of business planners and psychologists for many decades, however, limited work exists on integrating this knowledge into autonomous systems. Providing this contextual knowledge of human factors can potentially be used to predict and adapt in response to changes and variation between Human Operators.

Application of intelligence in this context requires the reconciliation of multiple domains. The following framework is proposed, to outline the necessary interactions and connectivity between different systems, to effectively collect, store, interpret, and act in an appropriate manner on data that can be extracted from a manufacturing process.

Within a typical manufacturing control process, multiple elements can be identified. Typically, these elements can be divided into two areas, *data* collection, and *Robotics*. Existing control systems receive binary signals from sensors (data collection), which are passed to a PLC, which responds in a preprogrammed fashion(robotics). We propose the addition of an intermediary *Cognitive Layer* containing several modular elements, to implement additional data processing and analytical steps. This will provide the *machine* in the Human-machine-interaction with agency, and enable *intelligent* response to changes in the perceived environment. These three layers can be reconciled into the illustrated framework shown in Figure.1, which illustrates the flow of information through the proposed system.

The framework divides the control system of a robotic operator into three main layers, the first, concerned with data generation and collection, an intermediary Cognitive Layer, and a third layer that accounts for the elements of robotic control, connecting the virtual to the physical, through traditional robotics techniques.

Data Collection: With *intelligent* systems, significant consideration must be given to the available data and its sources. The first layer of the framework encompasses data collection, which is a vast topic, with a large number of inherent problems. Within the scope of this framework, the specific method is not relevant, so long as the robotic operators' data controller has the capacity to gather and transfer multiple data instances, and is compatible with the formats and interfaces demanded by the computational components.

The available data can be considered as being generated and collected from two main sources: *Process data*; The data elements directly related to the parameters of the process; and *Environmental data*; any supplementary data deemed relevant. Notable consideration must be given to capturing and appropriately recording the relevant *Human Factors* data at this stage, which may be included in either of the above categories.

Almost all data collection systems will incorporate data storage. Reserves of *historical* data (which exists typically in a database format), must also be available to the data controller, and able to be passed through to the cognitive layer. The use of a corpus of historical data is necessary to enable the learning functionality. The vast majority of the capabilities of the previous three sections may be handled by existing data collection methods.

Cognitive Layer: The intermediary *cognitive layer* is based on the modular structure seen in existing cognitive architectures. Each of the modules combines multiple functions and is responsible for a different area of cognition. The first of these *modules*, receives data from the data collector through an information retrieval or input mechanism, before additional functions perform the necessary preprocessing transformations for the data to be useful to the cognitive controller. This is analogous to *Perception*, whereby the observed data and the information it contains is affected by the beliefs and aims of the observer. These transformations may, for instance, take the form of establishing a cycle time, by looking at the separation of execution of two different sensor activations. Additional information not directly dependent on observations, such as knowledge of shift patterns etc. is included in the dataset here.

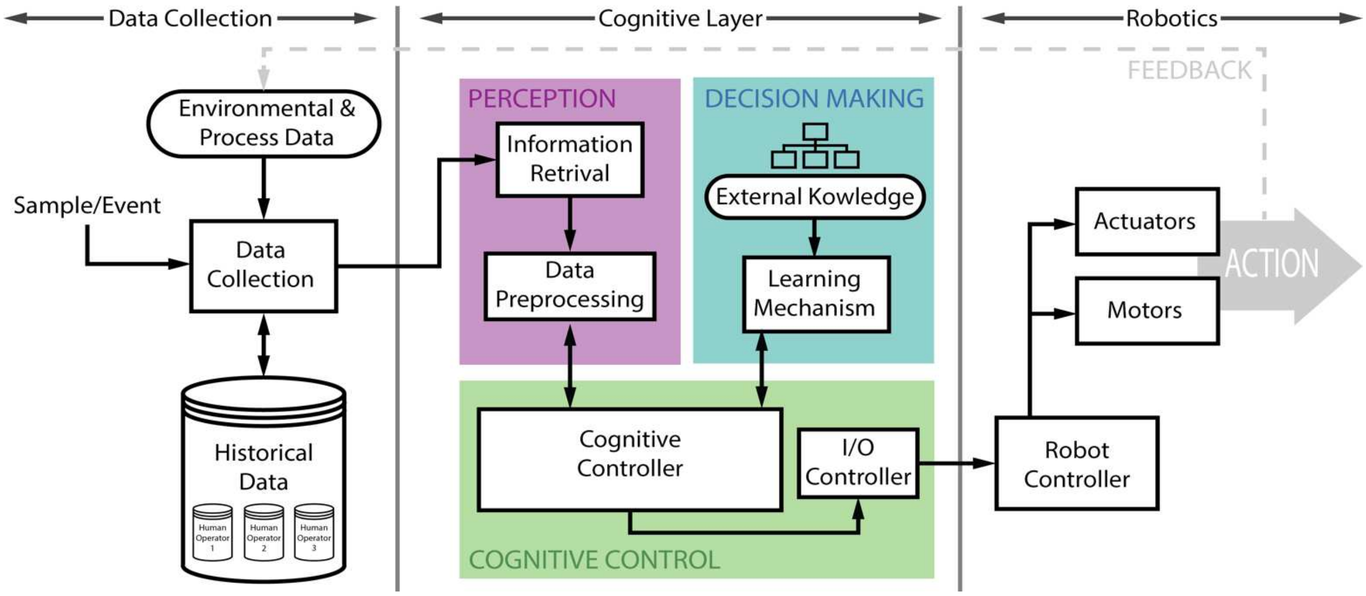

Figure.1. The proposed framework illustrated in terms of information flow through the system. Divided into three functional *layers.*

The decision-making module isolates the learning aspects of the cognitive layer. Isolation of the analytical cognitive processes more easily enables the integration with low-level control; the responsibility of the cognitive controller. The learning mechanism may be supported in decision making by additional knowledge, which is not directly observable by the agent. This may include additional contextual information, such as shift patterns or production targets. The *Perception* and *Decision-Making* modules are supported by an underlying *Cognitive Controller*, which manages the information flow through the cognitive layer. It manages requests for information and collates and exchanges the relevant data with the different modules to exhibit the necessary functionality, in addition to passing the relevant command instructions via an I/O controller to the robotic layer where they can be enacted.

Robotics: The decision processed by the cognitive controller is passed through an I/O controller, to convert the information to the necessary format. It is then passed to the direct, *Robotic Controller*. Separating these steps provides a clear distinction between the *digital* and *physical* domains of the system, and isolates the elements of *control planning*, (one of the modular elements of cognition identified in existing cognitive architectures) which are necessary to effect the correct motion of the robotic operator. This reduces computational load and facilitates the division of cognition into higher-level reasoning, and preserves necessary elements of *reactive* action, that can still be enacted by sensors directly connected the robot controller (i.e. in the case of kill-switches and collision/fault-detection). In many cases, these will be instructions sent to a Programmable Logic Controller (PLC) or another control system. By using established equipment from techniques from robotics and automation will facilitate implementation, and ensure legacy compatibility.
The commands are then sent by the PLC to the motors and actuators to affect the relevant motion of the robot. This results in an *action*, which influences the system, which will affect the recorded environmental and process data, forming a feedback loop.

The architecture proposed in this section demonstrates how an intermediary *cognitive layer,* can be integrated between the existing data acquisition and robotics elements of a manufacturing process, to provide intelligent, adaptive functionality, based on knowledge and real-time information of human factors. The presented case-study is intended to demonstrate the intended functionality of the framework and to assess the potential feasibility of inclusion of knowledge of human factors. The combined elements of the cognitive layer provide the necessary functionality to leverage this knowledge and improve production processes through adaptability.

4. Case Study

The following section of the paper seeks to apply the above framework to a generalized real-world scenario, to illustrate how the cognitive layer can be implemented into a production process. Simulation enables the testing of novel control systems, without the interference of real-world production. The case-study is based on a semi-automated production line, featuring human operators (HO) and robotic operators (RO), performing an assembly process in a sequential manner.

The simulation model is designed to represent a simplified manufacturing process interaction with an upstream and downstream position, and a non-specific manufacturing operation defined only by its duration at each position. The two operators are separated by a conveyor that doubles as a buffer zone (Figure.2). Each Operator has an associated *cycle time*, which enables performance by different HO's to be compared.

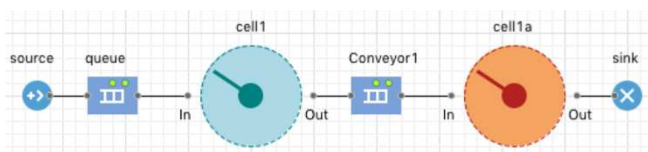

Figure.2. The model developed in AnyLogic, each cell contains a delay and data capture elements.

This simplified interaction is designed to assess the feasibility of our approach. This is a singular and dependent interaction, whereby the behavior of either individual can lead to lagging or bottlenecking when unaddressed by the other, due to the relative difference in the two levels of performance.

In such a scenario, intelligent behavior may be achieved by effecting changes in the behavior of the upstream RO, based on the performance of the HO working in the adjacent downstream position. By adjusting the RO's cycle time, a behavior can be effected in response to the actions of its partner, to counteract the lagging or bottlenecking that arises from disparity.

In the proposed framework, the affected behaviour is determined by the decision-making module of the cognitive layer in response to the capture of data supplied via the *perception* module. The data instance is processed by the cognitive controller and passed to the decision-making module, where the proposed learning model produces an estimate for the HO performance, based on the observed state. This is a non-trivial task, and the particular method will depend on the nature of the captured data. This information is passed back to the cognitive controller, where it is used to inform the instruction given to the Robotics layer to enact the relevant behavior; such as a change in the velocity of motion, to alter the cycle time of the RO to compensate as necessary.

The process and environment data collected is sampled each time a product is completed by the HO, and contains the previous Cycle Time, and elapsed shift duration; in addition, to other necessary values. Using this dataset, models of HO performance with respect to these values can be developed by learning elements in the decision-making module, which can be used to predict the optimal RO performance targets, based on the current HO performance. These targets in this instance are the current productivity; the total number of products leaving the system, and time idle; where the buffer is full and the RO cannot continue until space becomes available.

A model was developed for use with simulation software (AnyLogic), to represent and explore the interaction between and RO and HO, and investigate the impact of these factors. The modelled scenario consists of individual *Cells*, representative of each manufacturing station, the upstream cell having initially a fixed CT (CT_R), based on real-world timings of 35 seconds. The second Cell in the process, representing the HO, has a nominal CT of 45s (CT_H), which is normally distributed about the desired value, representative of variability in human performance between operations. The interstitial conveyor is modelled as a queue element, which contains a maximum of 10 products before becoming full, preventing any more products exiting the upstream cell.

In the first instance, static RO behavior was considered. Three HO’s were defined, with varying CT’s, one faster than nominal (HO_1 = 40s), one the same (HO_2 = 45s), and one slower (HO_3 = 50s), to represent variability amongst individuals. The impact of fatigue -both physical and cognitive- resulting from repetitive, precise action, was considered. This was incorporated by increasing the CT_H, by 10% and 20% for HO_2 and HO_3 respectively; over the duration of the simulation. Each simulated *shift* represents 2 hours of real-world time. Figure.3a illustrates the RO productivity and time spent Idle for each of the three operators.

The Figure illustrates the difference in productivity of the RO between operators, represented by the set of solid points.

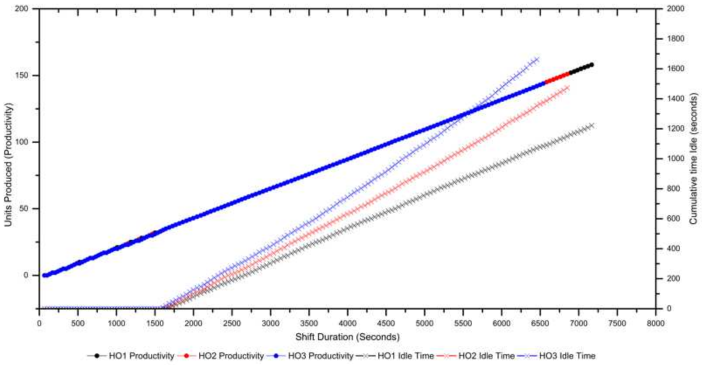

Figure.3. Effect of Variation and Fatigue in Human Operators on RO productivity and Idle Time over shift duration.

Which increases as expected with HO performance. The other set of crossed points illustrates the cumulative time spent idle by the RO. For all HO’s this value initially remains at zero, as the buffer between the two operators fills. Once this happens, the RO is forced to wait between operations, as there is nowhere for the current workpiece to go. The cumulative effects of small variations in performance can be seen in the diverging total idle time over the shift.

The simulation was repeated to examine the impact of adaptable behavior. To simulate the predictive performance of the proposed decision-making module generating a value for the target RO cycle time, CT_R is updated based on the CT_H of the previous product, modified by a normally distributed error of ±10% to approximate errors in the learning model predictions.

Adjustment of the RO behavior can be seen to minimize its overall idle time when used with the predicted HO values. However, the combined Cycle Time of each product is dictated by the downstream HO position, and as such, no benefits to productivity may be leveraged through alteration of RO behavior alone. Figure.4 shows that the conveyor is never filled during the shift, whilst some buffer is still required to account for variation and predictive errors, in the adaptable condition, bottlenecking can be reduced as at no point is the RO required to remain idle.

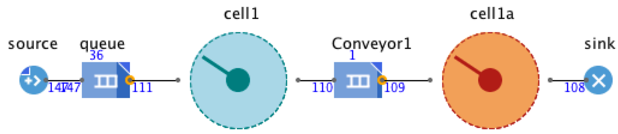

Figure.4. Screenshot from mid-simulation, the buffer element contains only 1 product, the free space resulting in no RO time spent idle.

5. Discussion & Conclusions

The work presented in this paper proposes a framework which provides an implementation of *intelligent* behavior, within the context of a manufacturing process. Through the inclusion of a *Cognitive Layer*, factors influencing human behavior can potentially be accounted for, and the control instructions altered to provide adaptable behavior. Through a case study, a generic, although not a representative application has been illustrated, which demonstrates how such a system may be implemented. Whilst the authors do concede that the current simulation model represents an ideally abstracted scenario, the work demonstrates that such behavior can beneficially impact production systems.

The reconciliation of multiple domains leads to many inherited problems, and many of these will need to be overcome before the presented approach is a technically sound implementation. Comprehensive further work is planned to further understand how models of cognition and applications of intelligence, can be utilized, to facilitate the collaborative efforts between robotic operators and their human counterparts. This includes developing a functional model for the *cognitive layer*; including a greater investigation into data handling and processing; work on developing an effective and capable learning element, incorporating elements of memory, and the consideration of additional decision–making capabilities, such as task-scheduling. More study of the mechanisms of human collaboration will be conducted and concepts explored with the generation of real data, improving understanding of the interaction dynamics. Additionally, ongoing generation of data will enable consideration of the historical working relationship (Represented by the archived performance data), with multiple operators to be considered by the learning model.

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